REAL-TIME INTRA-OPERATIVE 3D TISSUE DEFORMATION RECOVERY

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ABSTRACT

Since the advent of laparoscopy, surgical technology has advanced on an exponential scale that has broadened the accessibility of the surgeon to the operative field with minimal incisions. Minimally Invasive Surgery (MIS) is carried out through natural body openings or small artificial incisions. It achieves its clinical goals with minimal inconvenience to patients, which results in reduced patient trauma, shortened hospitalisation, improved diagnostic accuracy and therapeutic outcome. With the introduction of robotic assisted MIS, the use of image guided surgical navigation is becoming increasingly popular, but it needs to handle non-rigid tissue deformation over the course of the procedure. In this paper, a probabilistic framework is presented that combines the strengths of different depth cues for tissue deformation recovery. The practicality of the technique is demonstrated using *in vivo* stereo laparoscopy data. Real-time intra-operative application of this technique has benefits for image based adaptive navigation and motion stabilisation in robotic assisted surgery.

***Index Terms*—** robotic assisted surgery, image guided intervention, tissue deformation recovery, intra-operative navigation, computational stereo, surface reconstruction, belief networks.

1. INTRODUCTION

With recent advances in robotic assisted Minimally Invasive Surgery (MIS), the use of pre- and intra-operative imaging guidance is becoming increasingly popular for more effective surgical navigation and imposing dynamic active constraints for improved safety and accuracy in performing delicate surgical tasks [1]. Image based surgical navigation normally involves pre-operatively acquired patient data, but organ deformation due to instrument-tissue interaction requires real-time, intra-operative adaptation of the anatomical model [2]. In this regard, the use of intra-operative imaging is essential but it must be supplemented by 3D tissue deformation recovery of the operating field as current intra-operative imaging techniques (such as those provided by intra-operative ultrasound) are usually limited to selected imaging planes or volumes, often with a narrow field of view. Effective fusion of these data, coupled with the use of biomechanical modelling, facilitates the use of augmented reality for surgical visualisation and navigation, obviating the need of the surgeon to remove his/her eyes from the operating field to see beyond the exposed anatomical surface. The need for real-time intra-operative 3D tissue deformation is also motivated by the recent development of robotic assisted MIS for providing adaptive motion stabilisation for complex micro-surgical tasks such as beating heart coronary vessel anastomosis [3, 4]. This permits certain complex surgical tasks to be performed under a static frame of reference. Active constraints based on patient specific 3D data with *in situ*, dynamic adjustment further enhances the accuracy and safety of the procedure, thus avoiding accidental instrument motion violation in safety critical anatomical regions in the presence of large tissue deformation. This permits tighter margins of error whilst allowing a greater degree of freedom.

The purpose of this paper is to outline some of the major approaches to real-time tissue deformation recovery, and to introduce a Markov-Random Field (MRF) based Bayesian Network (BN) for combining depth cues from different depth recovery strategies in a probabilistic framework so as to achieve a more complete and accurate 3D deformation field.

2. *IN-VIVO* 3D DEPTH RECOVERY TECHNIQUES

In MIS procedures, surgeons have to rely on a narrow 2D camera view of the operating field and the perceptual cues that a surgeon uses to estimate depth include binocular disparity, convergence, linear perspective, elevation, shading, shadow and texture [5]. Exactly how humans acquire detailed knowledge of a 3D field from a 2D view has been the subject of study for many years. Because the majority of the cues involved are subtle and difficult to detect in the operative environment, it is not well understood how these cues are assimilated in MIS.

The determination of tissue deformation can be achieved with a number of different approaches that involve motion sensors such as mechanically/optically based accelerometers or marker based techniques that use suturing or projecting fiducals on the tissue surface. With the sophistication and miniaturisation in optical technologies, it has now become possible to seamlessly incorporate eye tracking capabilities into the surgical environment. It has been shown that eye gaze derived from binocular eye-tracking can be effectively used to recover 3D motion and deformation of the soft tissue during MIS [6, 7]. Since robotic assisted MIS typically involves a pair of miniaturized stereo cameras, detailed 3D motion and structure recovery from the stereo laparoscope with image registration has been proposed [8-10]. The major advantage of these methods is that they do not require additional modification to the existing MIS hardware, but computationally they introduce a more difficult machine vision problem of inferring dense 3D correspondence which is often ill-posed. Existing research has shown that sparse sets of well known feature correspondences can be used to enforce additional constraints, therefore significantly increases the accuracy and robustness of the technique. Furthermore, the integration of other visual cues such as shading, specular reflectance and their temporal characteristics in response to soft tissue deformation can further enhance the practical accuracy of the technique [11].

These different approaches to 3D tissue deformation recovery, however, all have certain limitations. For example, shading based techniques tend to perform well in regions with uniform albedo, little texture and smooth local curvature [12, 13]. Most approaches are based on strong smoothness constraints or require the assumption that the tissue surface within the field-of-view is continuous. Computational stereo based approaches, on the other hand, are more robust in regions that have distinctive geometrical features or sufficient texture details. Although some of the computational stereo methods are capable of reconstructing dense depth maps without requiring additional feature correspondence pairs, there is still the prerequisite that surfaces possess sufficiently detailed textures for 3D reconstruction to be effective. This is problematic when dealing with homogenous soft tissue surfaces. Accurate and robust 3D reconstruction of soft tissue deformation therefore requires that these complementing techniques to be effectively combined to be practically useful. To this end, a probabilistic framework based on MRF-BN can be used.

3. DEPTH FUSION WITH MRF-BN

As soft tissue often has smooth continuous surface and seldom has shape depth variations, the surface structure can be represented by a MRF and the conditional probability of a point $I_{x,y}$ can be formulated as:

$$P(I_{x,y} \mid I_{\Re_x,\Re_y}) = P(I_{x,y} \mid I_{A_{x,y}})$$

where $A_{x,y}$ represents the Markov blanket and $I_{A_{x,y}}$ represents the neighbouring nodes, where $x \in \Re_x$, $y \in \Re_y$ and $x, y \notin A_{x,y}$. A Markov blanket can be defined as:

$$A_{x,y} = (x+a, y+b)$$

where

$$a = -1,..,1 \quad b = -1,..,1 \quad and \quad a \neq b$$

The MRF is designed to maintain spatial continuity across an image, while the depth of each surface point is inferred via a Bayesian Network by fusing the posterior probabilities in the MRF from different depth cues. A belief propagation scheme is devised that uses the evidence represented by the sparse stereo points to infer the depth of the surrounding surface patches, and the propagation iterates until the full surface is recovered [14].

To demonstrate how the MRF-BN works in practice, the proposed technique has been applied to a phantom and an *in vivo* video sequence captured using a daVinci surgical robot, as shown in Figure 1. Figure 2 illustrates the captured laparoscopic image and the corresponding surface reconstruction results. Figure 2(b) illustrates the surface reconstruction result using only the shading information. As shown in the result images, the estimated tissue surfaces conform well to the structure perceived from the image, except in the specular highlight areas. To minimise the effect of specularities, a colour based filtering approach is used to remove the specularities, shown in Figure 2(c), and a B-Spline interpolation is used to recover the removed areas, shown in Figure 2(d).

Figure 3 illustrates an example of a 3D reconstruction result using the computational stereo technique [9]. To facilitate the visualisation of the sparse surface, a small texture patch is shown at each feature point. It can be seen that the method can cope with a large range of disparities as the overall algorithm can be implemented in a hierarchical manner where an image pyramid of four levels is constructed for each image and Lucas-Kanade matching is used to refine the correspondences at each level.

Although feature based stereo surface reconstruction can accurately estimate the 3D locations of distinctive feature points, they are not sufficient to reconstruct the entire 3D surface geometry. Figure 4 demonstrates the reconstructed tissue surface using the proposed MRF-BN method, and Figure 5 illustrates the result of applying the proposed technique to an *in-vivo* robotic assisted MIS sequence. It is evident from the figure that the proposed technique is able to reconstruct accurately the entire 3D surface, which is difficult to achieve by using individual depth cues.

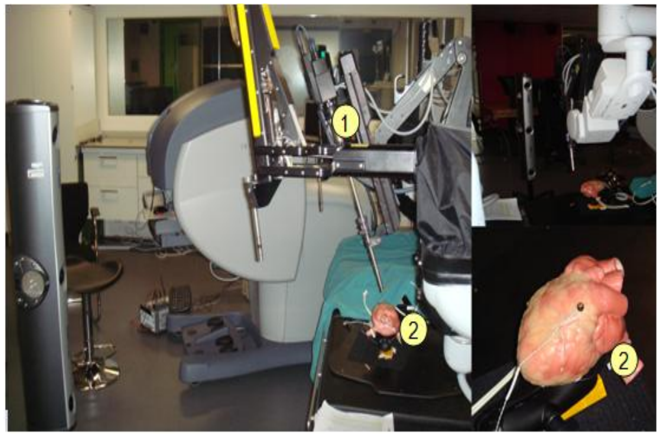
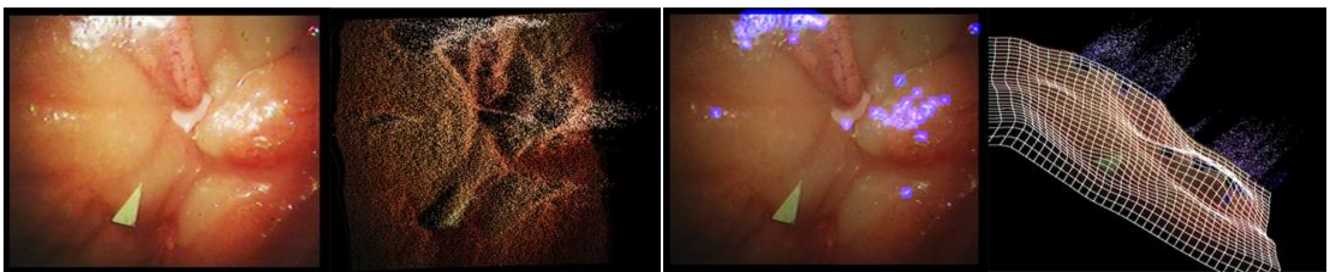


Figure 1. Experimental setup for tissue deformation recovery by using the proposed algorithm. The stereo laparoscopic camera of the daVinci robotic system (1) was used to capture the motion of a phantom heart (2).



(a) (b) (c) (d)

Figure 2. The captured laparoscopic image from the phantom sequence (a) and the corresponding surface reconstruction result (b) based on the shading information. It also illustrates the effect of specular highlights of the tissue surface (as highlighted in blue) (c) and the B-Spline surface interpolation results (d).

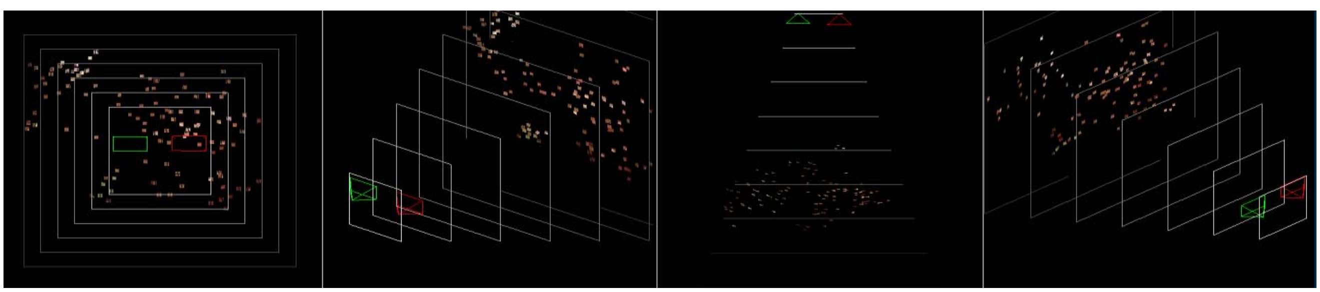


Figure 3. The 3D reconstructed result (in four different views) by using the sparse stereo method. Small texture patches are assigned to each reconstructed 3D point to improve visualisation and the locations of the cameras are highlighted in green and red. The grey squares (5mm apart) are used to indicate the depth of the surface with respect to the camera views.

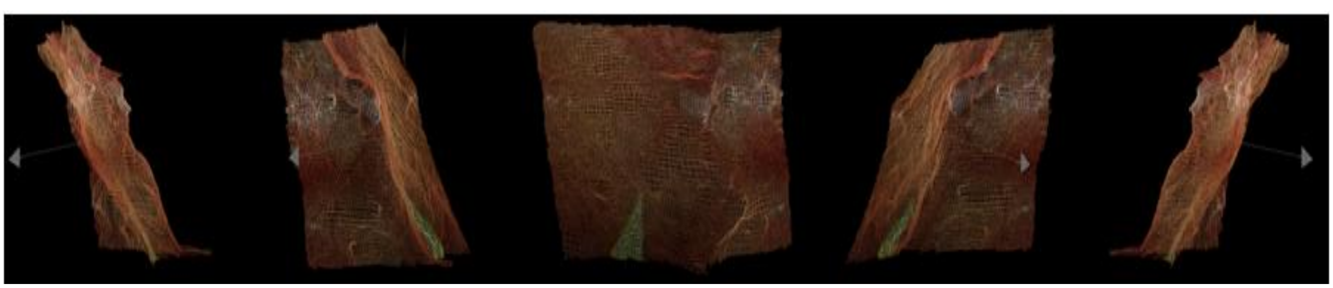
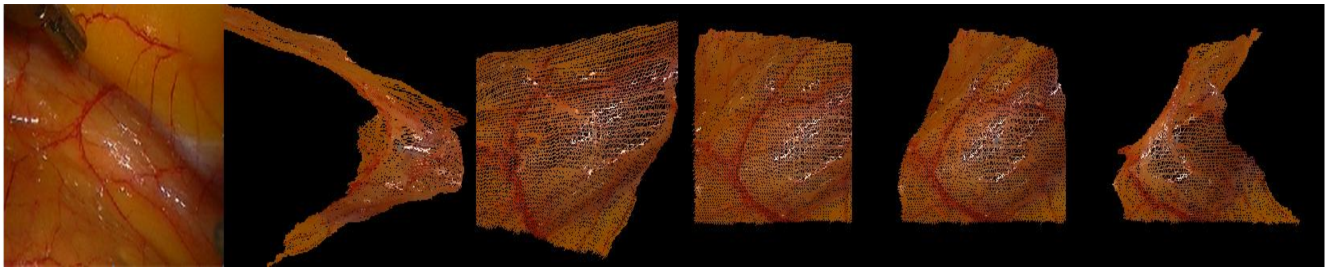


Figure 4 The surface reconstruction results by using the proposed MRF-BN technique.



(a) (b)

Figure 5 (a) An *in-vivo* laparoscopic sequence and (b) its corresponding surface reconstruction results.

4. DISCUSSION AND CONCLUSIONS

The complexity of the surgical environment implies that no single vision algorithm can handle the large tissue deformation involved in MIS. We have presented in this paper different approaches to real-time *in situ* tissue deformation recovery and the use of MRF-BN to combine different depth cues. A generalised formulation of this probabilistic framework will allow other vision models to be incorporated with a degree of flexibility that facilitates a trade off between speed, accuracy and robustness. Hence, tissue motion tracking systems can be tailored to specific intra-operative application according to the different requirements and practical constraints. With the advent of reliable vision-based real-time and *in situ in vivo* techniques on 3D-deformation recovery, this allows the use of optical based techniques for achieving adaptive motion stabilisation, active constraints, and intra-operative image registration under large tissue deformation. One promising goal is to devise a semi-automated motion-stabilised surgical-navigation system by fusing human-driven gaze contingent information with machine-interpreted visual cues, resulting in a level of accuracy and reliability superior to the fully automated counterpart, and without having to sacrifice real-time capability.

5. REFERENCES

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